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TRACKING SYSTEM USING TEXTURE CUE BASED ON WAVELET TRANSFORM

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Abstract: This paper presents an approach for tracking objects whose principal discriminate characteristic is its texture. The presented system extracts texture features based on the wavelet transform and uses a fuzzy grammar classifier. The feature vector consists of 6 characteristics extracted from the wavelet detail images. The overall system was integrated on the platform developed by sony – AIBO robot. This application ensures a real time tracking approach and can be parameterized in order to be flexible in face of different types of texture.

Keywords: robot vision, tracking applications, texture analysis, fuzzy grammar

1. INTRODUCTION

Object tracking is a crucial research issue in robot vision, especially for the applications where the environment is in continuous changing, like mobile robot navigation, and in applications that must deal with unstable grasps (Pressigout and Marchand, 2005). The most common approaches for object tracking are based mainly on the detection of one of following cues: edges, color and texture (Pressigout and Marchand, 2005; Taylor and Kleeman, 2003; Everingham and Thomas, 2001; Zhao and Tao, 2005; Yilmaz, *et al*, 2004).

The first one concerns the extraction of a number of features of the object, like points, lines, distances and models of the contours. Once this is generally based on the analysis of the gradients intensity, other techniques are necessary for applications with highly texture environments or objects (Pressigout and Marchand, 2005; Shahrokni, *et al*, 2004; Yilmaz, *et al*, 2004). Also for applications where the light conditions are not stable or its interaction with the objects produces shadows, the edge based techniques are not suitable as well.

When the color is the main different characteristic of the object in relation with the environment, the most suitable approaches are the ones based on this feature. Several works can be found in the literature extracting characteristics based on different color spaces (Zhao and Tao, 2005; Yilmaz, *et al*, 2004; Bradski, 1998).

Texture segmentation techniques are recently been applied to object tracking, especially as a complement to a multi-cue tracker (Giebel, *et al*, 2004; Shahrokni, *et al*, 2004; Everingham and Thomas, 2001). Texture segmentation techniques require computing statistics over image patches (which tends to be computationally intensive), and generally they use classification methods that require a time expensive off-line learning phase. Therefore such approach has not been felt suitable for tracking purposes.

This paper presents an application for tracking texture objects that intends to reduce the time consuming in the processing and in the off-line learning phases. The texture segmentation is based on features extracted from the detail images of the wavelet transform and on a fuzzy grammar as the classifier. Ferreira (2004) developed an industrial computer vision prototype for material inspection using this approach and a classification rate of 95% was accomplished.

The process is divided into two phases: a *learning* and an *tracking* phase. In the learning phase the texture for tracking is manually selected with an initial window being specified. The feature vector is extracted and a fuzzy rule that characterize the texture is determined. During the tracking phase the fuzzy rule is evaluated for the data that are present in the tracking window, which is dynamically adjusted.

As a case study the developed application was integrated with the AIBO robot platform. This platform is being used as a companion robot, and one of its tasks is to maintain surveillance over dependent people in a clutter environment. To maintain several moving persons under tracking the system will identify the specific cloths of each individual, meaning tracking the several textures that are present in the image.

2. SYSTEM ARCHITECTURE

Fig. 1 presents the architecture of the processing system, in which two paths were specified: one for the *learning phase* and another for the *Tracking phase*.

The *Feature Extraction* module is identical for both phases and extracts the feature vector that best describes each texture of the object. This module is applied only to the image ROI which is defined by the tracking window in the learning phase, and defined by to the search window (which is an enlarged version of the tracking window) during the tracking phase.

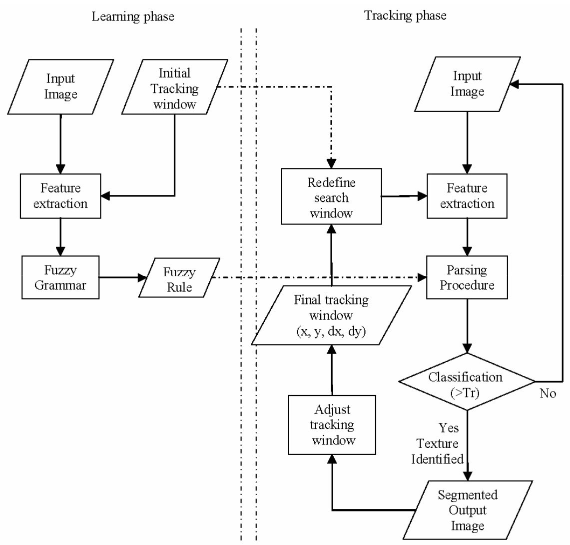


Fig 1. Architecture of the processing system.

The *Fuzzy Grammar* module generates the fuzzy rules that describe the texture.

In the *Tracking phase*, the feature vector is submitted to a *Parsing Procedure* module developed with the compilers yacc and lex (Appel, 1998; Bumble-Bee, 1999), i.e. the vector is submitted to the fuzzy rule and a response value is obtained. The parsing procedure was developed for this specific fuzzy grammar. The inputs are the feature vector extracted from the *Feature Extraction* module and the rule for the texture object to track. The output of the parsing procedure is a value in the interval [0,1] reflecting the grade of membership of the object.

The *Classification* module uses the output of the parsing and verifies if the rule has a response higher than a pre-defined threshold. The result is a binary image where the blob corresponds to the presence of the texture under tracking.

In order to track the texture in the next video frame the tracking window must be adjusted and an enlarged version of it is specified as the new ROI for the next image. The *Adjust Tracking Window* module is responsible for this operation and is presented in fig. 2. This procedure is similar to the one used in the CAMSHIFT algorithm (Bradski, 1998).

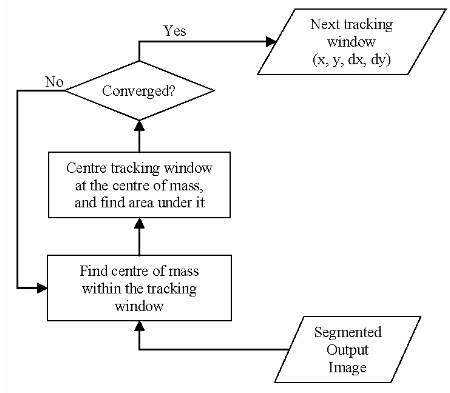


Fig. 2. Adjust tracking window module.

The centre of mass of the blob that is present in the segmented image is found. Next the tracking window is repositioned at this centre, and the area of the blob under the tracking window is quantified. This procedure is repeated until the area converges. The current size and position of the tracked object are reported to be used in the next video image.

3. FEATURE EXTRACTION

Besides the classical approaches for texture segmentation, like de ones that can be classified as statistical, structural and spectral (Ballard and Brown, 1982; Haralick and Shapiro, 1992; Pratt, 2001; Williams, 1999), new ones have been more recently under research. The most well formulated are based on wavelet transform (Wouwer, 1998) and Gabor filters (Teuner, *et al*, 1995). They have deserved special attention because of its analogy with the human vision system, which processes visual information in a multi-scale manner. The wavelet transform is one of the multi-resolution techniques more applied to image analysis, and specifically to texture segmentation (Randen, 1997; Wouwer, 1998; Livens, 1998).

Benedetto (1994) and Burrus (1998) present theoretical fundamentals of the wavelet transform applied to signal analysis. Fig. 3 summarizes the decomposition of a generic signal using the discrete wavelet transform (DWT). It can be viewed as the application of low-pass filters ($h_0[n]$) and high-pass filters ($h_1[n]$) followed by a sub-sampling.

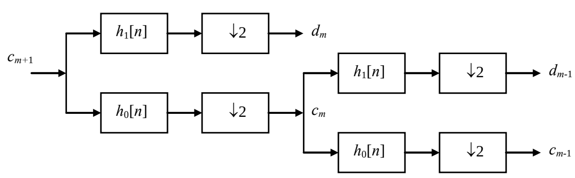


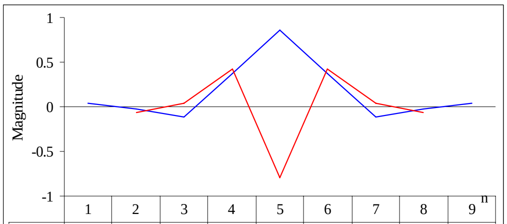
Fig. 3. Signal decomposition using DWT.

To deal with an image processing problem it is necessary to employ a two-dimensional DWT. With this approach an approximation coefficient, at level $m+1$, is decomposed in four components: the approximation coefficients at level m and the detail coefficients at level m in three orientations: horizontal, vertical and diagonal.

The feature vector consists of features extracted from the detail images at each decomposition level. Typically the extracted features are statistical parameters like mean, variance and energy. Wouwer (1998), Livens (1998) and Porter (1996) evaluated the use of different features and made a comparative analysis. They observed non major differences in which concerns efficiency.

Another important issue is what type of wavelet to use in texture segmentation. Livens (1998) supports that the type of function doesn't produce relevant changes in the analysis.

In this work the wavelet used consists in the two FIR filters presented in fig. 4. The feature extraction module uses three levels of decomposition and for each detail image the mean, standard deviation and four contrast values (Equation 1 to 6) where extracted. Fig. 5 shows a textured image and its correspondent wavelet transform for the G component.



	1	2	3	4	5	6	7	8	9
h0	0.03783	-0.0238	-0.1106	0.3774	0.8527	0.3774	-0.1106	-0.0238	0.03783
h1		-0.0645	0.04069	0.41809	-0.7885	0.41809	0.04069	-0.0645	

Fig. 4. Wavelets filters $h_0[n]$ and $h_1[n]$.

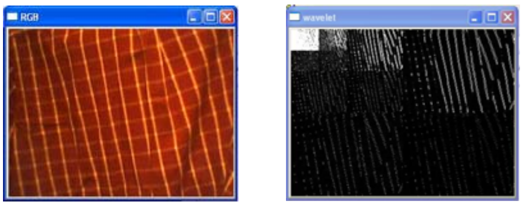


Fig. 5. Image of a textured object (left) and the corresponding wavelet transform (right) with three levels of decomposition.

$$M = \frac{1}{N}\sum_{i=0}^{N-1} I(i) \tag{1}$$

$$DP = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1}\left(I(i) - \bar{I}\right)^2} \tag{2}$$

$$CVSH = \frac{1}{N-1}\sum_{l=0}^{Nl-1}\sum_{c=0}^{Nc-1}\left|I(l \times Nc + c + 1) - I(l \times Nc + c)\right| \tag{3}$$

$$CVSV = \frac{1}{N-1}\sum_{l=0}^{Nl-1}\sum_{c=0}^{Nc-1}\left|I((l+1) \times Nc + c) - I(l \times Nc + c)\right| \tag{4}$$

$$CVAH = \frac{1}{N-1}\sum_{l=0}^{Nl-1}\sum_{c=0}^{Nc-1}\left|I(l \times Nc + c + 2) - I(l \times Nc + c)\right| \tag{5}$$

$$CVAV = \frac{1}{N-1}\sum_{l=0}^{Nl-1}\sum_{c=0}^{Nc-1}\left|I((l+2) \times Nc + c) - I(l \times Nc + c)\right| \tag{6}$$

Since the fuzzy grammar inference system implies that the magnitude of each element of the feature vector must be in the interval [0,1] a normalization is required:

$$\mu_F = F/255; \quad F \in \{M, DP, CVSV, CVSH, CVAV, CVAH\} \tag{7}$$

The feature vector to be presented to the fuzzy grammar module consists of 6×9 features for each color component: $P[\mu_{MijR}, \mu_{DPijR}, \mu_{CVSVijR}, \mu_{CVSHijR}, \mu_{CVAVijR}, \mu_{CVAHijR}, \mu_{MijG}, \mu_{DPijG}, \mu_{CVSVijG}, \mu_{CVSHijG}, \mu_{CVAVijG}, \mu_{CVAHijG}, \mu_{MijB}, \mu_{DPijB}, \mu_{CVSVijB}, \mu_{CVSHijB}, \mu_{CVAVijB}, \mu_{CVAHijB}]$, with i= 0, 1, 2; j= 0, 1, 2.

4. FUZZY GRAMMAR

The classifier must deal with the following constraints: a) high diversity of texture objects; b) the *learning phase* must be possible to be done with a unique sample of each type of texture.

The most common solutions use recognizers based on the calculus of metrics like Euclidean and Mahalanobis distance measures (Williams, 1999). However, these recognizers, as well as the ones based on neural, fuzzy logic and neurofuzzy networks, demand a great amount of samples from the population to perform learning.

In this work, a fuzzy system modelling approach was developed in which a fuzzy inference system identifies the fuzzy rules representing relationships among the features extracted from the wavelet detail images. There are several methods to generate these fuzzy rules. The most often applied are based on statistics, neural networks and genetic algorithms (Ivancic and Malaviya, 1998; Peters, *et al*, 1998; Looney, 2002). However, these poorly satisfy the needs of present application, specifically the possibility to learn using only a characteristic vector. Therefore, a fuzzy grammar approach was applied.

Fuzzy grammar is a pattern classification syntactic model used to represent the structural relations of patterns (Fu and Booth, 1986; Bezdek and Pal, 1992; Malaviya, 1996; Stanchev and Green, 2000) and describes the syntax of the fuzzy languages that generate the fuzzy rules.

For a full discussion see Lee and Zadeh (1969), Pal and Majumber (1986), Bezdek and Pal (1992), Yager and Zadeh (1992); herein, basic concepts of fuzzy grammar are only briefly reviewed. Fuzzy grammar GF is a quintuple $GF=(V_N, V_T, P, S_0, \mu)$, in which V_N and V_T are finite disjoint sets of non-terminal and terminal vocabulary respectively, such that $V=V_N \cup V_T$ is the total vocabulary of the grammar. P is a finite set of production rules of the type $\alpha \to \beta$, with $\alpha \in V_N$ and β is a member of the set V^* of all strings (including the null string ε). $S_0 \in V_N$ is the starting symbol. μ is the mapping of P→[0,1], such that $\mu(p)$ denotes the possibility of the current language sentence p∈P.

The syntax of the developed language $L(GF)$ is depicted in Fig. 6 and includes 4 different steps:

1) The codification of the features to primitives (Table I).

2) The definition of linguistic terms HistVar:# (LT). This setting is done according to Table II. The membership function ∏ is illustrated in Fig. 7 for one LT. The parameter c is chosen such that the eleven membership functions cover the all universe of discourse, X, and have disjointed maximums.

3) The definition of fuzzy modifiers (FM): "More than", "Less than" and "Between". The FM "More than" LT is defined by

$$\mu_{MT}\langle LT\rangle = \begin{cases} 1 & x \geq L \\ S(x, L-lb, L-lb/2, L & x < L \end{cases} \quad (8)$$

where L is a threshold value and lb is the bandwidth value of the S membership function (Bezdek and Pal, 1992; Malaviya, 1996). The *FM* "Less than" *LT* is given by

$$\mu_{LT}\langle LT\rangle = \begin{cases} 1 & x \leq L \\ 1-S(x, L, L+lb/2, L+lb & x > L \end{cases} \quad (9)$$

The *FM* "Between" LT_1 e LT_2, is given by

$$\mu_B < TL_1 >< TL_2 > \; = \begin{cases} 1-S(x, w_1, w_1+lb/2, w_1+lb) & x > w_1 \\ 1 & w_2 \leq x \leq w_1 \\ S(x, w_2-lb, w_2-lb/2, w_2) & x < w_2 \end{cases} \quad (10)$$

where w_1 and w_2 are threshold values (Bezdek and Pal, 1992; Malaviya, 1996).

4) The definition of fuzzy operators (*FO*) which define the relations between the linguistic terms and primitives. The following *FO* were defined:

a) &, representing the AND of two primitives. It is given by the Yager intersection (Pal and Majumber 1986).

b) >, representing "More than" *LT* and is given by μ_{MT}<*LT*>.

c) <, means "Less than" *LT* and is given by the function μ_{LT}<*LT*>.

d) | |, describes "Between two" *LT* and is given by μ_B<LT_1><LT_2>.

e) #, means a "Separator between a" *primitive* and a *LT*.

f) ( ), imposes a hierarchy in the rule.

Language -> $L(G_F) = \{x, \mu(x) | x \in V^*_T, S \Rightarrow x\}$

$G_F=(V_N,V_T,P,S_0,\{\mu\})$

VN={S0, Name, ElementSet ,Primitive, TermSet, Element, Term}

VT={ FWD00MEDFR, …, HistVar:1,..HistVar:11,+,..,#}

S0→ 'Rule' RuleName' 'ElementSet

ElementSet	→	ElementSet '&' ElementSet
		'('ElementSet {'|' ElementSet }')'
		'('ElementSet { '+' ElementSet } ')'
		Element
		λ
Element	→	TermSet '#' Primitive
		Primitive
TermSet	→	'>' Term
		'<' Term
		'('Term '| |' Term')'
RuleName	→	Obj1
		other
Primitive	→	FWD00MEDFR, FWD00MEDFG
		other
Term	→	'HistVar:1' ... 'HistVar:11'

Fig. 6. Syntax of the developed fuzzy language *L*(*GF*).

Table I. Codification of features to primitives, with *i*=0,1,2; *j*=0,1,2; *f*=*R,G,B*

Feature	Primitive
μ_{Mijf}	FWDijMEDFf
μ_{DPijf}	FWDijDPFf
$\mu_{CVSVijf}$	FWDijCVSVFf
$\mu_{CVSHijf}$	FWDijCVSHFf
$\mu_{CVAVijf}$	FWDijCVAVFf
$\mu_{CVAHijf}$	FWDijCVAHFf

Table II. Linguistic Terms

Designation	Function
HistVar:1	Π(x,0.2,0.0)
HistVar:2	Π(x,0.2,0.1)
HistVar:3	Π(x,0.2,0.2)
HistVar:4	Π(x,0.2,0.3)
HistVar:5	Π(x,0.2,0.4)
HistVar:6	Π(x,0.2,0.5)
HistVar:7	Π(x,0.2,0.6)
HistVar:8	Π(x,0.2,0.7)
HistVar:9	Π(x,0.2,0.8)
HistVar:10	Π(x,0.2,0.9)
HistVar:11	Π(x,0.2,1.0)

Consider as an example the texture depicted in Fig. 5. Fig. 8 illustrates the primitive FWD00MEDFR. This primitive has non-zero degrees of membership for *LT* HistVar:1, *LT* HistVar:2 and *LT* HistVar:3. The highest fuzzy value is obtained using *LT* HistVar:1. Thus, HistVar:1# FWD00MEDFR is part of the fuzzy rule which characterizes this texture.

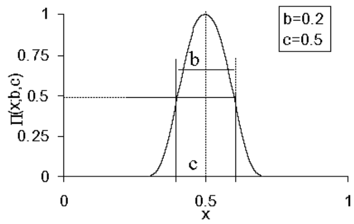


Fig. 7. Membership function ∏ for HistVar:6.

If more than one linguistic term gives fuzzy values superior to 0.75; a fuzzy modifiers like "More than", "Less than" and "Between", is applied to combine the obtained results. For the primitive FWD22SNCYF1 presented in fig. 9 the result will be <HistVar:2#FWD22SNCYF1.

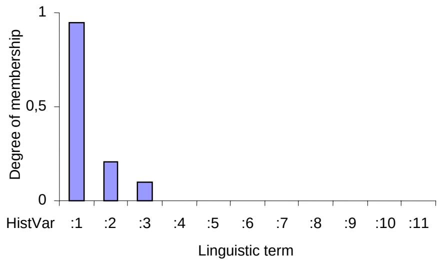


Fig. 8. The highest fuzzy value for LV FWD00MEDFR is obtained using LT HistVar:1.

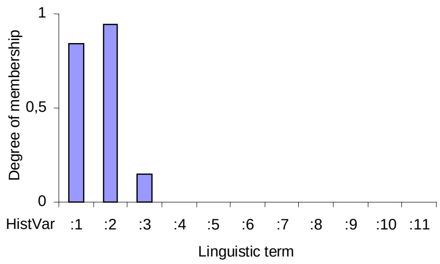


Fig. 9. Fuzzy value for *LV* FWD22SNCYF1.

5. IMPLEMENTATION ISSUES

When defining the initial tracking window (learning phase - Fig 1) it is necessary to have in consideration the type of texture, mainly in which concerns its

periodical or random behaviour. Therefore the following was settled: 1) the tracking area was divided in non-overlapping windows (NOW), whose size is a parameter that depends on the texture (Fig. 10a); 2) for each NOW the wavelet transform was applied, and the 6x9 features for each color component were extracted. When more than one NOW was specified each element of the final feature vector is the mean value of each feature; 3) a fuzzy rule was created with the feature vector.
In the tracking phase the search window was also divided in windows with the same size as the ones of the learning phase, but now overlapped (Fig. 10b). (*dx, dy*) ensures different grades of performance.

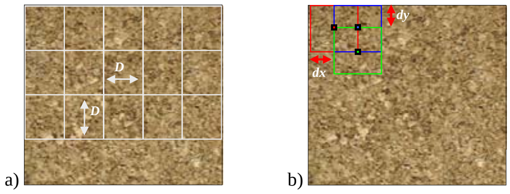


Fig. 10. Decomposition process of the tracking window for the application of the DWT. a) learning phase. b) tracking phase, (*dx,dy*): Red (0,0); Blue (D/2,0); Green (D/2,D/2).

The application was developed in C++, and was integrated with the AIBO platform. This platform uses wi-fi wireless connectivity and a vision system with an image size of 412x320 pixels and acquisition step through wi-fi of 57ms.

6. EXPERIMENTAL RESULTS

The feasibility and efficiency of the texture segmentation procedure have been studied by performing a set of experiments using different types of textures (Fig. 11). The graphic of fig. 12 shows the response of each texture rule (gray bars) as well as the overall response of the rule that characterize the other textures (red bars). A total of 100 patches for each texture were used.

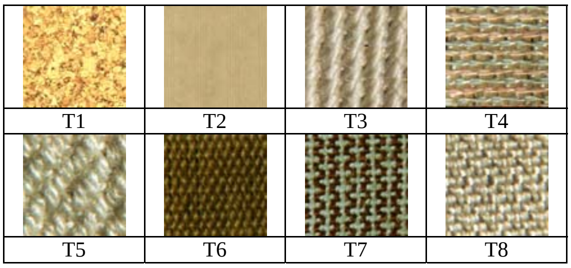


Fig. 11. Some examples of the textures used to texture segmentation procedure evaluation.

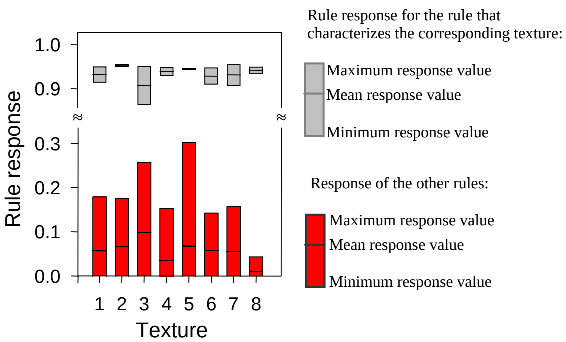


Fig. 12. Rule response for the images of fig. 11.

The advantage of this process is that when a texture is presented to the inference system it gives a response with high value (>0.85) for the rule that describes that texture. The rules corresponding to the other textures give low value responses (<0.3). This means that the system creates disjoints rules and assures a good classification. The above results show that the developed approach can be applied to different type of texture and also when the environment has several types of texture.
Fig. 13 and fig 14 exemplify the application integrated with the AIBO platform. The image of fig. 13a was acquired by the camera of the AIBO robot, and image 13b results from the application of the wavelet transform with a decomposition window of 45x34 pixels to the G component. The blue box in figure 13c defines the tracking texture. For the next video images the tracking procedure starts to search for this texture.

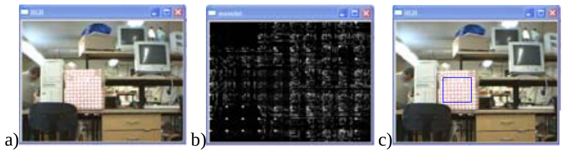


Fig. 13. Learning phase with the AIBO platform. a) Image of the object to track. b) Wavelet transform. c) Initial tracking window.

Fig. 14 shows a video frame, in which the box was moved to a different position, and the respective segmentation result.

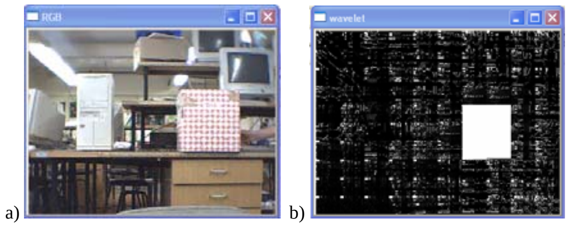


Fig. 14. Tracking phase with the AIBO platform. a) Image of the object to track. b) Segmentation result.

The application was tested with different illumination conditions and the results show that a drift in the illumination doesn't affect the efficiency of the segmentation procedure.

7. CONCLUSION

In this paper an application for tracking texture objects was presented. An important aspect involved is the reduce time consuming in the processing and in the off-line learning phases, which is a crucial factor for tracking. The texture segmentation is based on 6 features extracted for each detail image of the wavelet transform and on a fuzzy grammar used as classifier. The application was integrated with the AIBO platform, with an image size of 412x320 pixels and wavelet decomposition with 3 levels and window size of 45x34 pixels. With these specifications a processing time of 40ms was achieved which is less than the sensorial cycle of the platform.
Future work concerns the integration of this tracking cue with color features based on the hue component

histogram. Such approach will allow an improvement in the global tracking performance.

REFERENCES

Appel, A.W. (1998), *Modern compiler implementation in C*, Cambridge University Press, Cambridge.

Ballard, D.H. and C.M. Brown (1982), *Computer vision*, Prentice Hall, New Jersey.

Benedetto, J.J. and M.W. Frazier (1994), Wavelets mathematics and applications: CRC Press, 1994.

Bradski, G.R. (1998), Computer vision face tracking as a component of a perceptual user interface. In Workshop on Applications of Computer Vision, pages 214–219, Princeton, NJ, Oct. 1998.

Bumble-Bee (1999), *Parser Generator Manual* [online], Bumble-Bee Software, Available from http://www.bumblebeesoftware.com.

Burrus, C.S., R.A. Gopinath and H. Guo (1998), Introduction to wavelets and wavelets transforms, a primer: Prentice-Hall, 1998.

Bezdek, J.C. and S.K. Pal (1992), *Fuzzy Models for pattern recognition*, IEEE Press. New York.

Everingham, M. and B. Thomas (2001), Supervised Segmentation and Tracking of Non-rigid Objects using a "Mixture of Histograms" Model. In: Proceedings of the 8th IEEE International Conference on Image Processing (ICIP 2001), -, editor, pages 62--65. IEEE, October 2001.

Ferreira, M.J. (2004), *Desenvolvimento de um protótipo para a identificação, classificação e quantificação de defeitos, aplicável em ambiente industrial*, Unpublished Thesis (PhD), Universidade do Minho, Braga.

Fu, K.S. and T.L. Booth (1986), "Grammatical inference: introduction and survey, Part I, II", *IEEE Transactions on pattern analysis and machine intelligence*, vol. PAMI 8, n. 3, pp. 343-375.

Giebel, J., D.M. Gavrila and C. Schnörr (2004), A Bayesian Framework for Multi-Cue 3D Object Tracking, Proc. of the European Conference on Computer Vision, Prague, Czech Republic, 2004.

Haralick, R.M. and L.G. Shapiro (1992), Computer and robot vision, vol. 1: Addison-Wesley Publishing Company.

Ivancic, F. and A. Malaviya (1998), "An Automatic Rule Base Generation Method for Fuzzy Pattern Recognition with Multi-phased Clustering", in *IEEE Conference of Knowledge Engineering System*, *Proceedings of KES'98*, IEEE Press, Adelaide, pp 66-75.

Lee, E.T. and L.A. Zadeh 1969), "Note on fuzzy languages", *Information Sciences,* Vol. 1, pp. 421-434.

Livens, S. (1998), "Image analysis for material characterization", PhD Thesis, vol. 1, Universitaire Instelling Antwerpen, Antwerpen, Belgium.

Looney, C.G. (2002), "Pattern Recognition", in Hyngsuck Cho, (Ed.), Opto-Mechatronic Systems Handbook: Technical Applications - Handbook Series for Mechanical Enginnering, Vol 10, CRC Press.

Malaviya, A. (1996), *On-line handwriting recognition with a fuzzy feature description language*, PHD Thesis, Technische Universitat Berlin, Berlin.

Pal, S.K. and D.K. Majumber (1986), *Fuzzy mathematical approach to pattern recognition*, Halsted Press Book, John Wiley & Sons, New Delhi.

Peters, L., C. Leja and A. Malaviya (1998), "A Fuzzy Statistical Rule Generation Method for Handwriting Recognition", *Expert Systems Journal*, Elsevier Press, Vol. 15, nº. 1, pp. 1591-1604.

Porter, R. and N. Canagarajah (1996), "A robust automatic clustering scheme for image segmentation using wavelets", IEEE transactions on image processi*ng*, vol. 5, n. 4, pp. 662-665, 1996.

Pratt, W. K. (2001), Digital Image Processing, 3ed: Wiley Interscience, New York.

Pressigout, M. and E. Marchand (2005), Real-time planar structure tracking for visual servoing: a contour and texture approach. In IEEE/RSJ Int. Conf. on Intelligent Robots and Systems, IROS'05, August, 2005.

Randen, T. (1997), "Filter and filter bank design for image texture recognition", PhD Thesis, Stavanger College, University of Science and Technology, Stavanger, Norway.

Shahrokni, A., T. Drummond, and P. Fua (2004), Proc. Eur. Conf. on COmputer Vision, "Texture Boundary Detection for Real-Time Tracking", Prague, Czech Republic, May 2004.

Stanchev, P. L. and D. Green Jr (2000), "Formal languages for image primitives description", International journal information theories and applications, vol. 9, n. 2 pp. 51-60.

Taylor, G. and L. Kleeman (2003), "Fusion of multimodal visual cues for model-based object tracking", 2003 Australasian Conference on Robotics and Automation, Brisbane, 1-3 December 2003.

Teuner, A., O. Pichler and B.J. Hosticka (1995), "Unsupervised Texture segmentation of images using tuned matched gabor filters", IEEE transactions on image processing, vol. 4, n. 6, pp. 863-870.

Williams, P.S. (1999), The automatic hierarchical decomposition of images into sub-images for use in image recognition and classification, PHD Thesis, University of Western Australia.

Wouwer, G. V. (1998), "Wavelets for multiscale texture analysis", PhD Thesis, Universitaire Instelling Antwerpen, Antwerpen, Belgium.

Yager, R.R. and L.A. Zadeh (ed) (1992), An introduction to fuzzy logic applications in intelligent systems, Kluwer Academic, Boston.

Yilmaz, A., X. Li and M. Shah (2004), Contour-based object tracking with occlusion handling in video acquired using mobile cameras, Pattern Analysis and Machine Intelligence, IEEE Transactions on, Nov. 2004, Volume: 26, Issue: 11 On page(s): 1531- 1536

Zhao, Q. and H. Tao (2005), "Object tracking using color correlogram", to appear in IEEE Workshop on VS-PETS, October 2005.